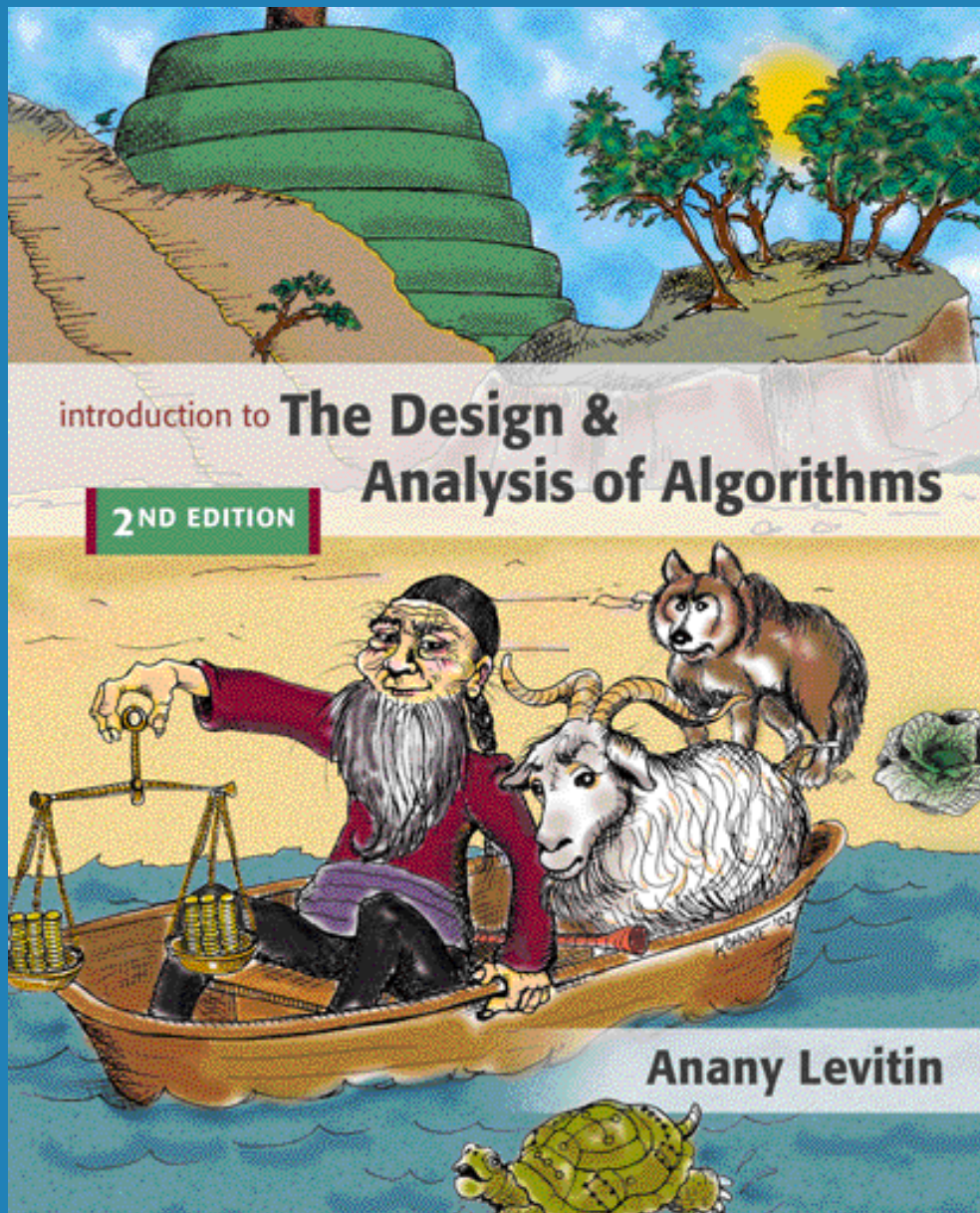


# Chapter 8

## Dynamic Programming



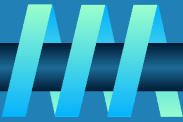
# Dynamic Programming



*Dynamic Programming* is a general algorithm design technique for solving problems defined by recurrences with overlapping subproblems

- Invented by American mathematician Richard Bellman in the 1950s to solve optimization problems and later assimilated by CS
- “Programming” here means “planning”
- Main idea:
  - set up a recurrence relating a solution to a larger instance to solutions of some smaller instances
  - solve smaller instances once
  - record solutions in a table
  - extract solution to the initial instance from that table

# Example: Fibonacci numbers



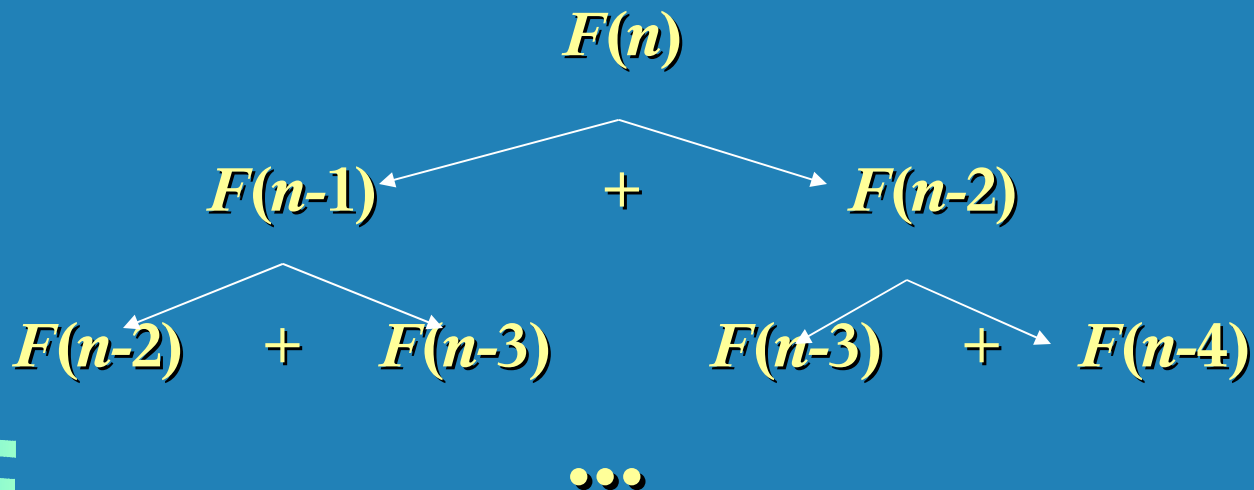
- Recall definition of Fibonacci numbers:

$$F(n) = F(n-1) + F(n-2)$$

$$F(0) = 0$$

$$F(1) = 1$$

- Computing the  $n^{\text{th}}$  Fibonacci number recursively (top-down):



# Example: Fibonacci numbers (cont.)

Computing the  $n^{\text{th}}$  Fibonacci number using bottom-up iteration and recording results:

$$F(0) = 0$$

$$F(1) = 1$$

$$F(2) = 1+0 = 1$$

...

$$F(n-2) =$$

$$F(n-1) =$$

$$F(n) = F(n-1) + F(n-2)$$

0	1	1	. . .	$F(n-2)$	$F(n-1)$	$F(n)$	
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Efficiency:

- time

- space

# Examples of DP algorithms



- **Computing a binomial coefficient**
- **Warshall's algorithm for transitive closure**
- **Floyd's algorithm for all-pairs shortest paths**
- **Constructing an optimal binary search tree**
- **Some instances of difficult discrete optimization problems:**
  - **traveling salesman**
  - **knapsack**

# Computing a binomial coefficient by DP

Binomial coefficients are coefficients of the binomial formula:

$$(a + b)^n = C(n,0)a^n b^0 + \dots + C(n,k)a^{n-k}b^k + \dots + C(n,n)a^0 b^n$$

Recurrence:  $C(n,k) = C(n-1,k) + C(n-1,k-1)$  for  $n > k > 0$

$$C(n,0) = 1, \quad C(n,n) = 1 \text{ for } n \geq 0$$

Value of  $C(n,k)$  can be computed by filling a table:

	0	1	2	...	$k-1$	$k$
0	1					
1	1	1				
.						
.						
.						
$n-1$					$C(n-1,k-1)$	$C(n-1,k)$
$n$						$C(n,k)$



# analysis



**ALGORITHM** *Binomial*( $n, k$ )

//Computes  $C(n, k)$  by the dynamic programming algorithm

//Input: A pair of nonnegative integers  $n \geq k \geq 0$

//Output: The value of  $C(n, k)$

**for**  $i \leftarrow 0$  **to**  $n$  **do**

**for**  $j \leftarrow 0$  **to**  $\min(i, k)$  **do**

**if**  $j = 0$  **or**  $j = i$

$C[i, j] \leftarrow 1$

**else**  $C[i, j] \leftarrow C[i - 1, j - 1] + C[i - 1, j]$

**return**  $C[n, k]$

**Time efficiency:  $\Theta(nk)$**

**Space efficiency:  $\Theta(nk)$**

# Knapsack Problem by DP



Given  $n$  items of

integer weights:  $w_1 \ w_2 \ \dots \ w_n$

values:  $v_1 \ v_2 \ \dots \ v_n$

a knapsack of integer capacity  $W$

find most valuable subset of the items that fit into the knapsack

Consider instance defined by first  $i$  items and capacity  $j$  ( $j \leq W$ ).

Let  $V[i,j]$  be optimal value of such instance. Then

$$\max \{V[i-1,j], v_i + V[i-1,j-w_i]\} \quad \text{if } j-w_i \geq 0$$

$V[i,j] =$

$$V[i-1,j]$$

$$\text{if } j-w_i < 0$$

Initial conditions:  $V[0,j] = 0$  and  $V[i,0] = 0$



# Knapsack Problem by DP (example)



Example: Knapsack of capacity  $W = 5$

<u>item</u>	<u>weight</u>	<u>value</u>
1	2	\$12
2	1	\$10
3	3	\$20
4	2	\$15

	capacity $j$					
	0	1	2	3	4	5
0						
1						
2						
3						
4						?

$w_1 = 2, v_1 = 12$     1

$w_2 = 1, v_2 = 10$     2

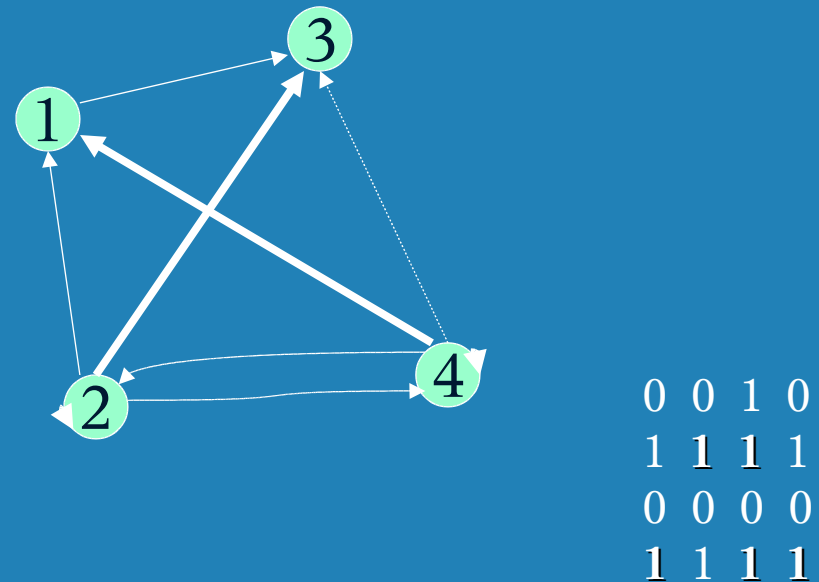
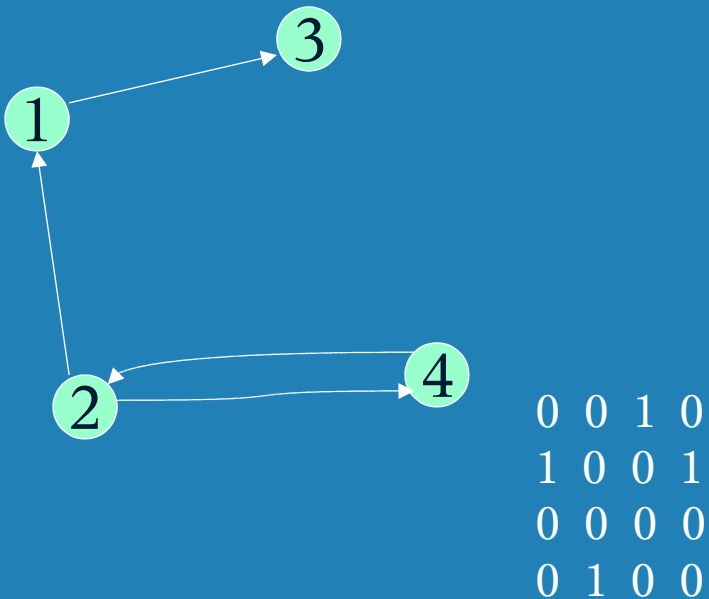
$w_3 = 3, v_3 = 20$     3

$w_4 = 2, v_4 = 15$     4

# Warshall's Algorithm: Transitive Closure



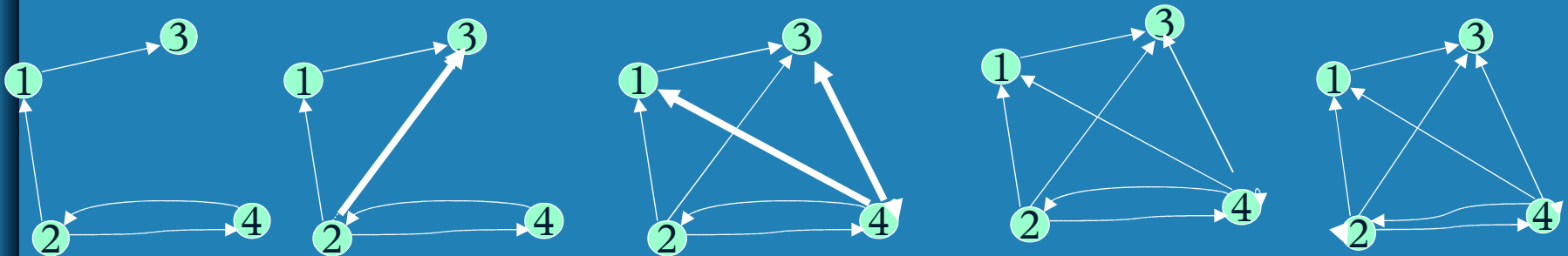
- Computes the transitive closure of a relation
- Alternatively: existence of all nontrivial paths in a digraph
- Example of transitive closure:



# Warshall's Algorithm

Constructs transitive closure  $T$  as the last matrix in the sequence of  $n$ -by- $n$  matrices  $R^{(0)}, \dots, R^{(k)}, \dots, R^{(n)}$  where  $R^{(k)}[i,j] = 1$  iff there is nontrivial path from  $i$  to  $j$  with only first  $k$  vertices allowed as intermediate

Note that  $R^{(0)} = A$  (adjacency matrix),  $R^{(n)} = T$  (transitive closure)

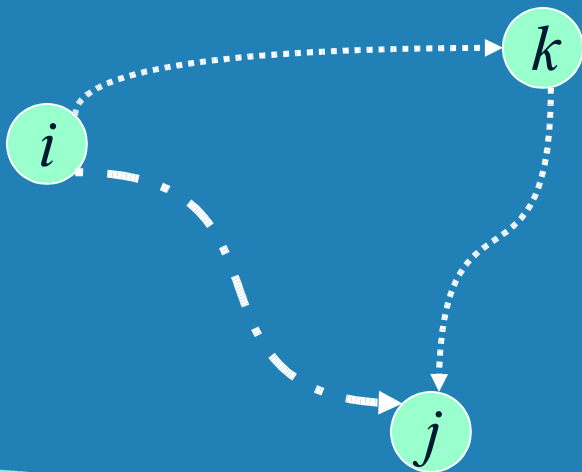


$R^{(0)}$	$R^{(1)}$	$R^{(2)}$	$R^{(3)}$	$R^{(4)}$
0 0 1 0	0 0 1 0	0 0 1 0	0 0 1 0	0 0 1 0
1 0 0 1	1 0 1 1	1 0 1 1	1 0 1 1	1 1 1 1
0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
0 1 0 0	0 1 0 0	1 1 1 1	1 1 1 1	1 1 1 1

# Warshall's Algorithm (recurrence)

On the  $k$ -th iteration, the algorithm determines for every pair of vertices  $i, j$  if a path exists from  $i$  and  $j$  with just vertices  $1, \dots, k$  allowed as intermediate

$$R^{(k)}[i,j] = \begin{cases} R^{(k-1)}[i,j] & \text{(path using just } 1, \dots, k-1) \\ \text{or} \\ R^{(k-1)}[i,k] \text{ and } R^{(k-1)}[k,j] & \text{(path from } i \text{ to } k \\ & \text{and from } k \text{ to } i \\ & \text{using just } 1, \dots, k-1) \end{cases}$$



# Warshall's Algorithm (matrix generation)



Recurrence relating elements  $R^{(k)}$  to elements of  $R^{(k-1)}$  is:

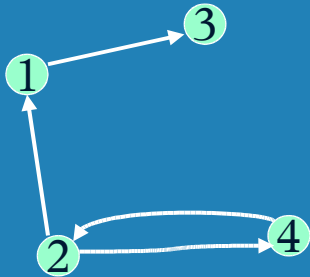
$$R^{(k)}[i,j] = R^{(k-1)}[i,j] \text{ or } (R^{(k-1)}[i,k] \text{ and } R^{(k-1)}[k,j])$$

It implies the following rules for generating  $R^{(k)}$  from  $R^{(k-1)}$ :

**Rule 1** If an element in row  $i$  and column  $j$  is 1 in  $R^{(k-1)}$ , it remains 1 in  $R^{(k)}$

**Rule 2** If an element in row  $i$  and column  $j$  is 0 in  $R^{(k-1)}$ , it has to be changed to 1 in  $R^{(k)}$  if and only if the element in its row  $i$  and column  $k$  and the element in its column  $j$  and row  $k$  are both 1's in  $R^{(k-1)}$

# Warshall's Algorithm (example)



$$R^{(0)} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

$$R^{(1)} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

$$R^{(2)} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 \end{bmatrix}$$

$$R^{(3)} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 \end{bmatrix}$$

$$R^{(4)} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 \end{bmatrix}$$

# Warshall's Algorithm (pseudocode and analysis)

**ALGORITHM** *Warshall*( $A[1..n, 1..n]$ )

//Implements Warshall's algorithm for computing the transitive closure

//Input: The adjacency matrix  $A$  of a digraph with  $n$  vertices

//Output: The transitive closure of the digraph

$R^{(0)} \leftarrow A$

**for**  $k \leftarrow 1$  **to**  $n$  **do**

**for**  $i \leftarrow 1$  **to**  $n$  **do**

**for**  $j \leftarrow 1$  **to**  $n$  **do**

$R^{(k)}[i, j] \leftarrow R^{(k-1)}[i, j] \text{ or } (R^{(k-1)}[i, k] \text{ and } R^{(k-1)}[k, j])$

**return**  $R^{(n)}$

**Time efficiency:**  $\Theta(n^3)$

**Space efficiency:** Matrices can be written over their predecessors

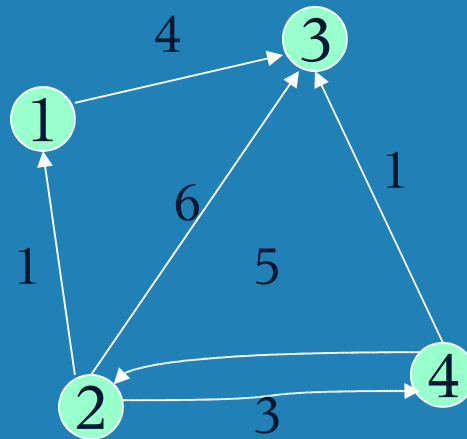


# Floyd's Algorithm: All pairs shortest paths

**Problem:** In a weighted (di)graph, find shortest paths between every pair of vertices

**Same idea:** construct solution through series of matrices  $D^{(0)}$ , ...,  $D^{(n)}$  using increasing subsets of the vertices allowed as intermediate

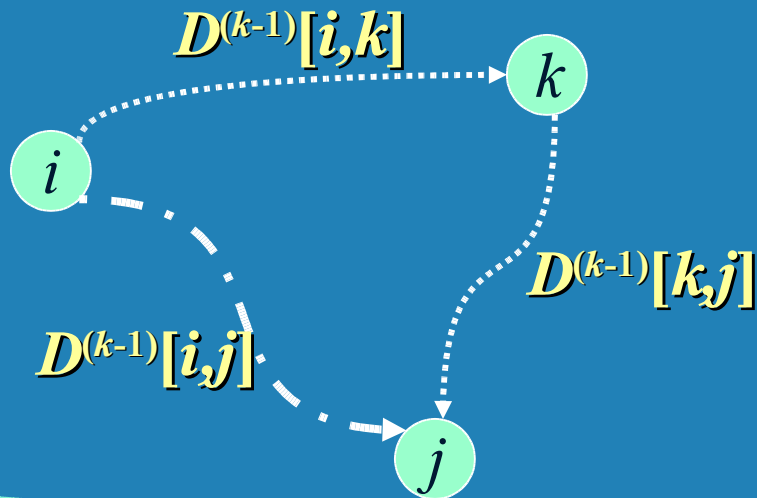
**Example:**



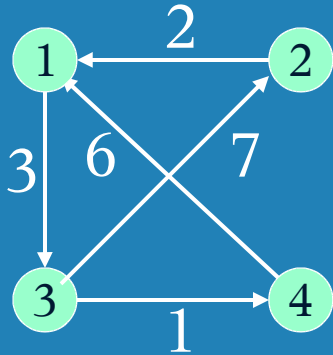
# Floyd's Algorithm (matrix generation)

On the  $k$ -th iteration, the algorithm determines shortest paths between every pair of vertices  $i, j$  that use only vertices among  $1, \dots, k$  as intermediate

$$D^{(k)}[i,j] = \min \{D^{(k-1)}[i,j], D^{(k-1)}[i,k] + D^{(k-1)}[k,j]\}$$



# Floyd's Algorithm (example)



$$D^{(0)} =$$

0	$\infty$	3	$\infty$
2	0	$\infty$	$\infty$
$\infty$	7	0	1
6	$\infty$	$\infty$	0

$$D^{(1)} =$$

0	$\infty$	3	$\infty$
2	0	5	$\infty$
$\infty$	7	0	1
6	$\infty$	9	0

$$D^{(2)} =$$

0	$\infty$	3	$\infty$
2	0	5	$\infty$
9	7	0	1
6	$\infty$	9	0

$$D^{(3)} =$$

0	10	3	4
2	0	5	6
9	7	0	1
6	16	9	0

$$D^{(4)} =$$

0	10	3	4
2	0	5	6
7	7	0	1
6	16	9	0

# Floyd's Algorithm (pseudocode and analysis)

**ALGORITHM** *Floyd*( $W[1..n, 1..n]$ )

//Implements Floyd's algorithm for the all-pairs shortest-paths problem

//Input: The weight matrix  $W$  of a graph with no negative-length cycle

//Output: The distance matrix of the shortest paths' lengths

$D \leftarrow W$  //is not necessary if  $W$  can be overwritten

**for**  $k \leftarrow 1$  **to**  $n$  **do**

**for**  $i \leftarrow 1$  **to**  $n$  **do**

**for**  $j \leftarrow 1$  **to**  $n$  **do**

$D[i, j] \leftarrow \min\{D[i, j], D[i, k] + D[k, j]\}$

**return**  $D$

**Time efficiency:**  $\Theta(n^3)$

**Space efficiency:** Matrices can be written over their predecessors

**Note:** Shortest paths themselves can be found, too

# Optimal Binary Search Trees



**Problem:** Given  $n$  keys  $a_1 < \dots < a_n$  and probabilities  $p_1 \leq \dots \leq p_n$  searching for them, find a BST with a minimum average number of comparisons in successful search.

Since total number of BSTs with  $n$  nodes is given by  $C(2n, n) / (n+1)$ , which grows exponentially, brute force is hopeless.

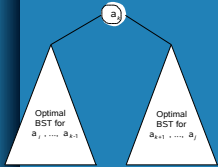
**Example:** What is an optimal BST for keys  $A, B, C$ , and  $D$  with search probabilities 0.1, 0.2, 0.4, and 0.3, respectively?

# DP for Optimal BST Problem



Let  $C[i,j]$  be minimum average number of comparisons made in  $T[i,j]$ , optimal BST for keys  $a_i < \dots < a_j$ , where  $1 \leq i \leq j \leq n$ .

Consider optimal BST among all BSTs with some  $a_k$  ( $i \leq k \leq j$ ) as their root;  $T[i,j]$  is the best among them.



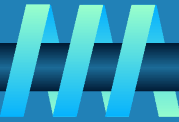
$$C[i,j] =$$

$$\min_{i \leq k \leq j} \{p_k \cdot 1 +$$

$$\sum_{s=i}^{k-1} p_s (\text{level } a_s \text{ in } T[i,k-1] + 1) +$$

$$\sum_{s=k+1}^j p_s (\text{level } a_s \text{ in } T[k+1,j] + 1)\}$$

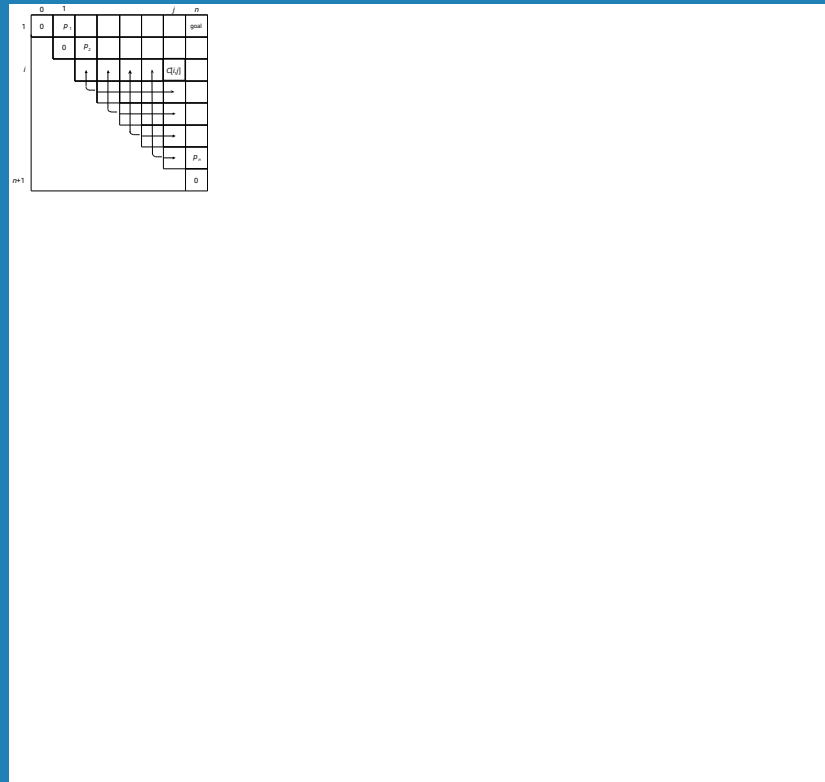
# DP for Optimal BST Problem (cont.)



After simplifications, we obtain the recurrence for  $C[i,j]$ :

$$C[i,j] = \min_{i \leq k \leq j} \{C[i,k-1] + C[k+1,j]\} + \sum_{s=i}^j p_s \quad \text{for } 1 \leq i \leq j \leq n$$

$$C[i,i] = p_i \quad \text{for } 1 \leq i \leq j \leq n$$





**Example:** key            *A*   *B*   *C*   *D*  
                          probability   0.1   0.2   0.4   0.3

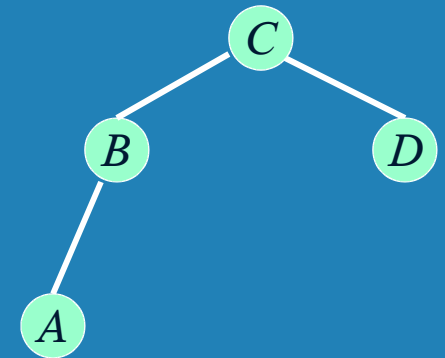
The tables below are filled diagonal by diagonal: the left one is filled using the recurrence

$$C[i,j] = \min_{i \leq k \leq j} \{C[i,k-1] + C[k+1,j]\} + \sum_{s=i}^j p_s, \quad C[i,i] = p_i;$$

the right one, for trees' roots, records *k*'s values giving the minima

<i>i</i> \ <i>j</i>	0	1	2	3	4
1	0	.1	.4	1.1	1.7
2		0	.2	.8	1.4
3			0	.4	1.0
4				0	.3
5					0

<i>i</i> \ <i>j</i>	0	1	2	3	4
1		1	2	3	3
2			2	3	3
3				3	3
4					4
5					



optimal BST

# Optimal Binary Search Trees



**ALGORITHM** *OptimalBST*( $P[1..n]$ )

```
//Finds an optimal binary search tree by dynamic programming
//Input: An array  $P[1..n]$  of search probabilities for a sorted list of  $n$  keys
//Output: Average number of comparisons in successful searches in the
//       optimal BST and table  $R$  of subtrees' roots in the optimal BST
for  $i \leftarrow 1$  to  $n$  do
     $C[i, i - 1] \leftarrow 0$ 
     $C[i, i] \leftarrow P[i]$ 
     $R[i, i] \leftarrow i$ 
 $C[n + 1, n] \leftarrow 0$ 
for  $d \leftarrow 1$  to  $n - 1$  do //diagonal count
    for  $i \leftarrow 1$  to  $n - d$  do
         $j \leftarrow i + d$ 
         $minval \leftarrow \infty$ 
        for  $k \leftarrow i$  to  $j$  do
            if  $C[i, k - 1] + C[k + 1, j] < minval$ 
                 $minval \leftarrow C[i, k - 1] + C[k + 1, j]$ ;  $kmin \leftarrow k$ 
             $R[i, j] \leftarrow kmin$ 
             $sum \leftarrow P[i]$ ; for  $s \leftarrow i + 1$  to  $j$  do  $sum \leftarrow sum + P[s]$ 
             $C[i, j] \leftarrow minval + sum$ 
return  $C[1, n], R$ 
```

# Analysis DP for Optimal BST Problem

**Time efficiency:**  $\Theta(n^3)$  but can be reduced to  $\Theta(n^2)$  by taking advantage of monotonicity of entries in the root table, i.e.,  $R[i,j]$  is always in the range between  $R[i,j-1]$  and  $R[i+1,j]$

**Space efficiency:**  $\Theta(n^2)$

**Method can be expended to include unsuccessful searches**